

Wave force prediction effect on the energy absorption of a wave energy converter with real-time control

Liang Li, Zhiming Yuan, Yan Gao, Xinshu Zhang

Abstract— Real-time control has been widely adopted to enlarge the energy extraction of a wave energy converter (WEC). In order to implement a real-time control, it is necessary to predict the wave excitation forces in the close future. In many previous studies, the wave forces over the prediction horizon were assumed to be already known, while the wave force prediction effect has been hardly examined. In this paper, we investigate the effect of wave force prediction on the energy absorption of a heaving point-absorber WEC with real-time latching control. The real-time control strategy is based on the combination of optimal command theory and first order-one variable grey model GM(1,1). It is shown that a long prediction horizon is beneficial to the energy absorption whereas the prediction deviation reduces extracting efficiency of the WEC. Further analysis indicates that deviation of wave force amplitude has little influence on the WEC performance. It is the phase deviation that leads to energy loss. Since the prediction deviation accumulates over the horizon, a moderate horizon is thus recommended.

Index Terms— real-time control, wave energy converter, energy absorption, renewable energy, wave force prediction

I. Introduction

It is expected that the global demand for energy will climb up to 25 percent by 2040 and the world is pursuing economic and renewable energy sources to keep up with this considerable demand growth [1]. Among various of ocean energy resources, sea waves take the advantage of high power density and all-day availability. To extract energy from ocean waves, WECs with various operation mechanisms have been developed. Li et al. [2] showed the power output of an oscillating-body WEC installed on a spar-type floating wind turbine. Boren et al. [3] presented a testing of a scaled vertical axis pendulum WEC. He et al. [4] utilized a floater breakwater to harvest energy from the waves. Experimental study of the concept was performed.

Control action is introduced to the WEC to enlarge the energy absorption and broaden the bandwidth. Babarit et al. [5] studied how the declutching control influenced the energy absorption of a WEC in regular and irregular waves. Zou et al. [6] investigated constrained and unconstrained optimal control of a heaving point-absorber. Park et al. [7] proposed an phase

control by estimating the wave period using velocity and acceleration information.

The latching control was first proposed by Budal and Falnes [8]. They found that one condition for maximizing energy absorption was to keep the velocity in phase with the wave excitation force. Therefore, the latching control is a kind of phase control. Hoskin and Nichols [9] used optimal command theory to derive the optimal latching duration. Babarit and Clement [10] assessed the benefits produced by the latching control. Greenhow and White [11] studied the relationship between energy absorption and latching duration in regular waves. Babarit et al. [12] compared different latching control strategies of a WEC in random sea. In these studies, the wave forces over the entire simulation interval were given so that the control law was deduced in advance. This kind of control scheme is commonly known as the optimal control. Another category of control strategy, namely the real-time control, determines the control law at every time step based on the prediction of wave information in the near future. Tom et al. [13] optimized the power capture of an oscillating surge WEC using the pseudo-spectral control method. Henriques et al. [14] applied latching control to an oscillating-water-column WEC. Son and Yeung [15] applied a real-time control to a point-absorber by adjusting the PTO damping. Although the control law was deduced at each time step in these studies, the wave forces were still given artificially so that the wave force prediction effect was omitted.

The application of a real-time control requires knowledge of future wave force information. Various models have been developed for wave prediction although it is a pity that they are hardly applied in WEC real-time control. Tsai et al. [16] forecasted the waves among multi-stations. Fusco and Ringwood [17] came up with a linear autoregressive model, which implicitly considered the cyclical behavior of waves. Ge and Kerrigan [18] predicted the wave elevations using autoregressive moving average model. Halliday et al. [19] utilized the fast Fourier transformation to predict the random sea waves. A wave prediction model based on the grey model was developed by Truong and Ahn [20]. This type of method is by nature a random signal processing technique so that it is applicable to various variables, including wave excitation force.

The importance of wave force information, especially the

L. Li, Z. M. Yuan (corresponding author), and Y. Gao, are with Department of Naval Architecture, Ocean and Marine Engineering, University of Strathclyde, (e-mail: liang.li@strath.ac.uk; zhiming.yuan@strath.ac.uk; yan.gao@strath.ac.uk).

X. S. Zhang, is with School of Naval Architecture, Ocean and Civil Engineering, Shanghai Jiao Tong University (e-mail: xinshuz@sjtu.edu.cn).

phase information, has drawn the attentions of researchers. Zhang *et al.* [21] investigated the effect of wave force on control sequence. Nevertheless, the controller was not real-time and the control sequence was deduced offline. Sang *et al.* [22] showed that the energy absorption of a slider-crank WEC was maximized when the generator rotation was in phase with wave forces. Song *et al.* [23] developed a multi-resonant controller by matching the impedance of the generator. Their control criterion was also that the velocity should be in phase with the wave forces. The sensitivity of a reactive controller to wave force information was examined by Fusco and Ringwood [24].

If a real-time control is to be incorporated to a true WEC in the real practice, the wave forces must be predicted and the prediction effect on the WEC performance should be considered. This study includes the wave force prediction in the real-time latching control strategy and investigates the forecasting effect on energy absorption. Prediction horizon and deviation are two crucial aspects of the wave force prediction. The study aims to investigate how the two factors influence the energy capture performance of the WEC.

II. NUMERICAL MODELLING

A heaving point-absorber is considered in this paper (see Fig. 1). The floater, rigidly connected to the power take-off (PTO) system fixed at the sea bed, is a hemisphere with a radius of $r = 5$ m. The floater draft is 5 m at the equilibrium position. Only heave motion of the WEC is allowed.

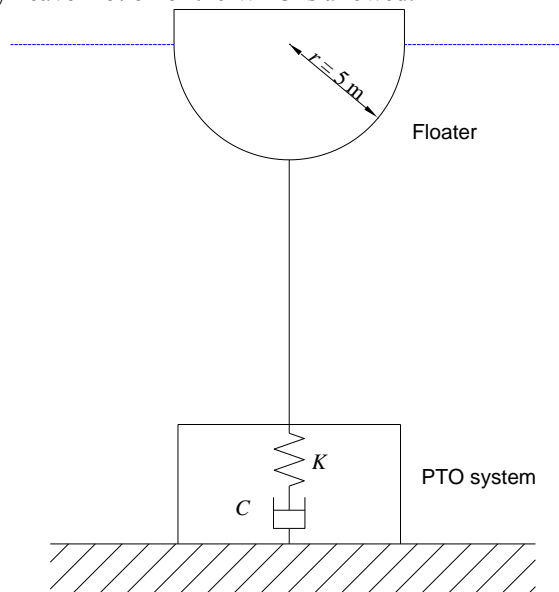


Fig. 1. Wave energy converter.

The PTO system is simplified as a damper-spring system, with damping coefficient C and stiffness K , which is a reasonable simplification of the permanent-magnet linear generator [25]. The Lorentz force acting on a moving point charge q with velocity \mathbf{v} in magnetic field \mathbf{B} is given by $q\mathbf{v} \times \mathbf{B}$, which can be regarded as a damping force. Also, the mechanical facilities will also provide the restoring stiffness. According to Vicente *et al.* [26], the stiffness of a PTO system is typically around ten percentage of the hydrostatic coefficient. Therefore, $K = 0.1\rho g\pi R^2$ is adopted. To harvest as much energy as possible, $C = 8.14 \times 10^5$ kN·s/m is used. The latching action is represented

by a very large but finite damping coefficient c .

The time-domain motion equation of the floater is represented with the state-space model

$$\dot{x} = \gamma \cdot x + \eta$$

$$\gamma = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{\rho g \pi R^2 + K}{M+m} & -\frac{C+\beta c}{M+m} & -\frac{R}{M+m} \\ 0 & Q & P \end{bmatrix}, \eta = \begin{bmatrix} 0 \\ F \\ 0 \end{bmatrix} \quad (1)$$

where $x = [z, \dot{z}, u^T]^T$ is the state vector. z and \dot{z} are the displacement and velocity vectors. u is an intermediate variable with dimension $n \times 1$. P , Q , and R are all constant matrices with dimensions $n \times n$, $n \times 1$, and $1 \times n$. The calculation of P , Q , and R is also called system identification [27]. n is the system order selected in the system identification. In the present study, $n = 5$ is used. M is the mass of the floater and m is the added mass corresponding to infinite frequency. F is the wave excitation force. $\beta(t)$ is the binary control law. $\beta = 1$ means that the WEC is locked whereas the WEC is released with $\beta = 0$.

A linear wave model is adopted to generate the stochastic wave elevations, which consist of a set of regular wave components with various oscillating frequencies and phases

$$\eta(t) = \text{Re} \left[\sum_{j=1}^N A_j e^{i(\omega_j t + \varepsilon_j)} \right] \quad (2)$$

$$A_j = \sqrt{2S(\omega_j) d\omega}$$

where A_j , ω_j , and ε_j are the wave amplitude, frequency, and random phase of the regular wave component j . $S(\omega)$ is the JONSWAP wave spectrum. If ω_j is uniformly distributed over the wave frequency range, the stochastic wave elevations will start to repeat after a certain duration [28]. To address this issue, the correction technique in [29] is adopted here. The wave frequency range is first uniformly divided into N segments and ω_j is randomly distributed within segment j .

It is well-known that the wave excitation forces are independent from the motions so that it allows us to generate the time series of wave forces in advance

$$F(t) = \text{Re} \left[\sum_{j=1}^N \Psi(\omega_j) A_j e^{i(\omega_j t + \varepsilon_j)} \right] \quad (3)$$

in which Ψ is the transfer function of linear wave excitation force. In this work, the hydrodynamic analysis tool Wadam [30] is used to calculate the transfer function and other hydrodynamic coefficients. These coefficients are obtained by solving the boundary-value formula of the flow potential. Please refer to [30] for more details of the calculation procedure.

III. REAL-TIME LATCHING CONTROL

A. Optimal command theory

Assuming that the wave forces over an arbitrary interval $[t_1, t_2]$ are already known (no matter forecasted with a prediction model or given artificially), the ultimate goal of the control action is to maximize the average energy absorption by controlling the WEC according to an appropriate control sequence $\beta(t)$

$$\max P = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} C \cdot \dot{z}(t, \beta)^2 dt \quad (4)$$

From a mathematical point of view, it is required to find the maximum of P subject to constraint Eq. (1). Define a Hamiltonian H :

$$\begin{aligned} H &= C\dot{z}^2 + \lambda \cdot (\gamma x + \eta) \\ &= C\dot{z}^2 + \lambda_1 \dot{z} + \sum_{i=1}^n \left[\lambda_{i+2} \left(Q_i \dot{z} + \sum_{j=1}^n P_{ij} u_j \right) \right] \\ &\quad + \lambda_2 \left[\frac{F_{wave}}{M+m} - \frac{\rho g \pi r^2 + K}{M+m} z - \frac{C + \beta c}{M+m} \dot{z} - \frac{1}{M+m} \sum_{i=1}^n R_i u_i \right] \end{aligned} \quad (5)$$

λ is a state vector, which can be regarded as the Lagrange multipliers. From the Pontryagin maximum principle, the optimal β is the one maximizing the Hamiltonian at every time step throughout $[t_1, t_2]$. The Hamiltonian is a linear function of β so that β must be the extremal values (0 or 1) to maximize the Hamiltonian. It is easy to find that the Hamiltonian reaches the maximum value on condition that

$$\beta = \begin{cases} 1 & \lambda_2 c \dot{z} < 0 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

Applying the latching control, the PTO system switches abruptly between two states ($\beta = 0, 1$) so that it is a bang-bang control. Based on the already known wave force information, the time series of floater movement can be calculated. The next task is to calculate λ_2 and the associated control sequence. The state vector satisfies the following general relationships.

$$\dot{\lambda}_i = -\frac{\partial H}{\partial x_i}(t, x, \beta), i = 1, 2, \dots, n \quad (7)$$

$$\lambda(t_2) = \bar{0}$$

Eq. (7) is not an initial value problem because the final condition is given here. An iterative process is used to calculate λ . We first run the simulation without latching ($\beta = 0$) actions by integrating Eq. (1) forward from $t = t_1$ to $t = t_2$. Then, it is able to determine λ and β by integrating Eq. (7) backwards from $t = t_2$ to $t = t_1$ ($\lambda(t_2) = 0$ is now an initial condition). Iterate this process for sufficient times until the control sequence converges.

B. Real-time control

If the optimal command theory is applied over the entire interval $[0, T]$ then the obtained control sequence is the optimal one. It is the so-called optimal control, which is impossible in the real practice. Nevertheless, a prediction model allows us to apply the optimal command theory over a short interval in the close future, where the energy absorption is maximized. By receding and updating the horizon instantaneously, the real-time control is implemented (see Fig. 2). Such control algorithm is called receding horizon control or model predictive control.

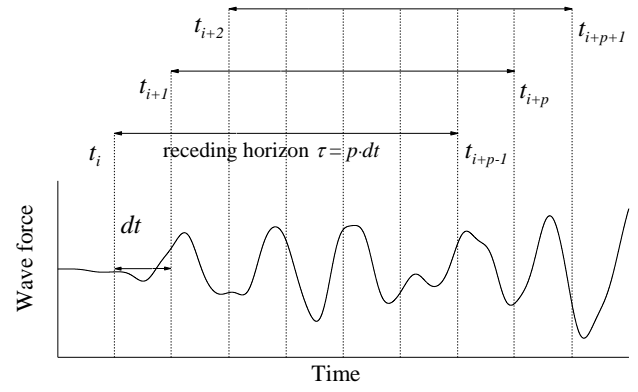


Fig. 2. Receding horizon control.

C. Wave force prediction

The first order-one variable grey model GM(1,1) is used to predict the wave forces over the receding horizon. In the grey prediction theory, the prediction is based on the collection of historical raw data without requirement of the mathematical model of the dynamic process. At time step t_i , start the forecasting process by collecting at least 4 consecutive raw data X over the past few seconds. Moreover, the raw data must be non-negative. To meet the requirement, a positive offset $O = 2 \times \max(|x_i|)$ is added to the raw data so that the data will be positive. The offset O is subsequently deducted from the predicted results at the end of the forecasting process.

$$X = (x_1, x_2, \dots, x_n) + O, n \geq 4 \quad (8)$$

Obtain an accumulated series Y from X

$$Y = (y_1, y_2, \dots, y_n) \quad (9)$$

$$y_k = \sum_{i=1}^k x_i, k = 1, 2, \dots, n$$

Create the so-called background series Z

$$Z = (z_2, z_3, \dots, z_n) \quad (10)$$

$$z_k = (y_k + y_{k-1}) / 2$$

Set the grey differential formula

$$x_k + a z_k = b, k = 2, 3, \dots, n \quad (11)$$

and acquire parameters a and b with the least square method. Establish the first order-one variable grey model GM(1,1) to predict the random signal within interval $[t_{i+1}, t_{i+p}]$

$$\begin{aligned} \hat{x}_{n+p} &= \hat{y}_{n+p} - \hat{y}_{n+p-1} - O \\ \hat{y}_{n+p} &= \left(y_1 - \frac{b}{a} \right) e^{-a(n+p-1)} + \frac{b}{a} \end{aligned} \quad (12)$$

where \hat{x}_{n+p} is the predicted data at time step t_{i+p} .

Practically, p is set to 1 indicating that only response at the next step is predicted. At time step t_i , collect raw data and predict the data at step t_{i+1} . Repeat the forecasting process at step t_{i+1} again to forecast the data at next step. By collecting raw data and predicting future data alternately, the grey model can provide accurate real-time prediction of the random signal. However, a real-time control strategy requires to forecast the wave forces over the coming future not just at the next time step. As shown in Fig. 3, the prediction deviation accumulates over the prediction horizon.

According to Eq. (6), the deduction of control sequence is based on the relationship between the velocity \dot{z} and the state

vector λ . Moreover, λ is a function of wave forces. Consequently, the control sequence is dependent on the velocity and the wave forces. Actually, the latching control is by nature a kind of phase control, which maximizes the energy absorption by regulating the WEC velocity and tuning it in phase with the wave forces. When the velocity and the wave forces are in phase with each other, the wave forces accelerate the WEC so that the WEC is set free. Otherwise, the wave forces hinder the movement so that the latching action should be applied. It is recognized as the criterion of latching control since the work of Budal and Falnes [8]. As shown in [8], the latching action is applied when the velocity vanishes and the WEC is released again once the velocity becomes in phase with the wave forces again. In the real practice, the control sequence must be deduced based on the predicted wave forces whereas the WEC is subject to the true wave forces, implying that the control sequence is not completely compatible with the WEC motion. That is to say, the control sequence based on wave force prediction may lock and release the WEC at the wrong instants. For example, the predicted wave forces are out phase with the velocity and thereby the control algorithm decides to the lock the WEC. However, the true wave forces are in phase with the velocity, in which condition the WEC should be released. Consequently, the effectiveness of the latching control is reduced and the latching control may even make a negative contribution to the energy absorption. Apparently, such effect is caused by the prediction error. The following part of this paper will investigate how the wave force prediction affects the WEC energy absorption.

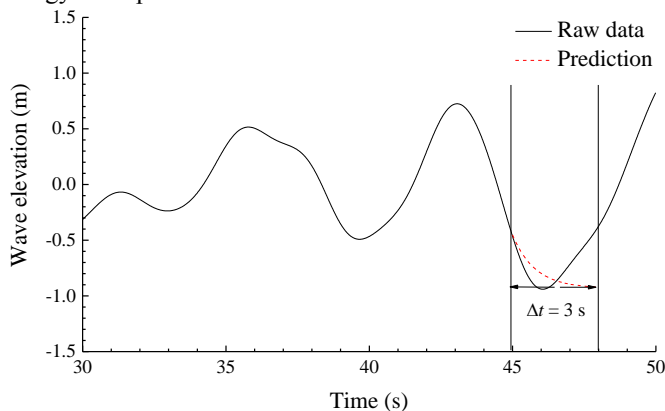


Fig. 3. Accumulation of prediction deviation.

IV. WAVE FORCE PREDICTION EFFECT

The effect of wave force prediction on the energy absorption of the WEC in both regular and irregular waves are investigated. The simulation length is set to 4000 s for irregular waves and only the last 3600 s data will be collected to eliminate the transient effects arising in the initial simulation stage. For regular waves, the simulation runs until the WEC reaches a steady state. The time step is 0.01 s. The wave amplitude is 1 m in regular wave cases. The random wave conditions considered in this paper are listed in Table I.

Table I
ENVIRONMENTAL CONDITIONS

	Case 1	Case 2	Case 3
Hs (m)	2	3	4
Tp (s)	6	8	10

A. Effect of prediction horizon

We first investigate the effect of prediction horizon. To eliminate the prediction deviation, the wave forces over the prediction interval are given so that the prediction deviation is totally omitted.

Fig. 4 illustrates the PTO system performance in regular waves. On the right side of resonant frequency, the real-time control makes little contribution of the enlargement of energy absorption regardless of prediction horizons. On the other side of resonant frequency, the energy capture performance is significantly improved with the application of real-time control. Babarit *et al.* [12] suggested that the optimal released duration in a single wave period was equal to half resonant period of the WEC on condition that the WEC was characterized of weak damping (the PTO damping coefficient C is sufficiently low). Therefore, the WEC won't be latched when the wave period is shorter than the resonant period of the WEC. Although the damping coefficient C in this paper is sufficiently high to harvest more wave energy, this property can still help to understand why the real-time control is mostly effective in low frequency regular waves. Fig. 5 interprets how the energy absorption is enhanced. Due to the latching action, the phase of WEC velocity is tuned and is now generally in phase with the wave excitation force so that the wave force will always accelerate the floater. Therefore, the WEC extracts more energy from the waves. The velocity is not exactly in phase with the wave force because we are applying a real-time control rather than an optimal control.

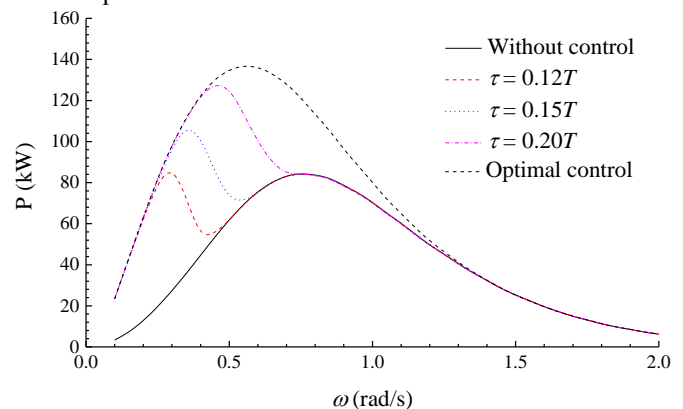


Fig. 4. Average energy absorption in regular waves with various prediction horizons, $T = 2\pi/\omega$.

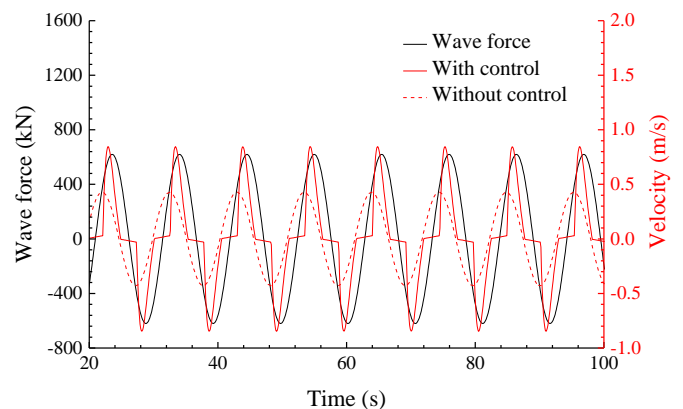


Fig. 5. Responses of the WEC in regular wave, $\omega = 0.6$ rad/s, $\tau = 0.2T$.

A notable feature in Fig. 4 is that the real-time control is more efficient with a long prediction horizon (The prediction horizon is represented by the percentage with respect to wave period). In fact, the receding horizon control can be regarded as a sub-optimal control. When the prediction horizon is as long as the entire simulation interval, the receding horizon control reduces to the optimal control. It is why the curves gradually converges to the optimal line with the increase of prediction horizon. Furthermore, long regular waves are more sensitive to the prediction horizon. As shown, a relatively short prediction horizon is sufficient in long wave to enlarge the energy absorption. For example, prediction horizon equal to 15% of the wave period can significantly increase the energy capture at $\omega = 0.3$ rad/s whereas it is not effective at all at $\omega = 0.6$ rad/s. Fig. 6 shows the effect of prediction horizon more clearly. The variation of energy absorption is characteristic of a sigmoid curve, in which three regions are identified. When the determination of control sequence is based on a short horizon length, the energy absorption remains relatively stable regardless of the expansion of prediction horizon. In this region, the control action is not effective at all as the energy absorption is identical to that without control. The performance of WEC is most sensitive to the prediction horizon within the middle region, where the energy absorption increases rapidly. As the prediction horizon continues increasing, the energy absorption gradually converges to the optimal level. Any further increase of receding horizon length has a very limited influence on the performance. By checking the slope of the curves within the middle segment, it manifests that the energy absorption is indeed more sensitive to the prediction horizon at long regular waves.

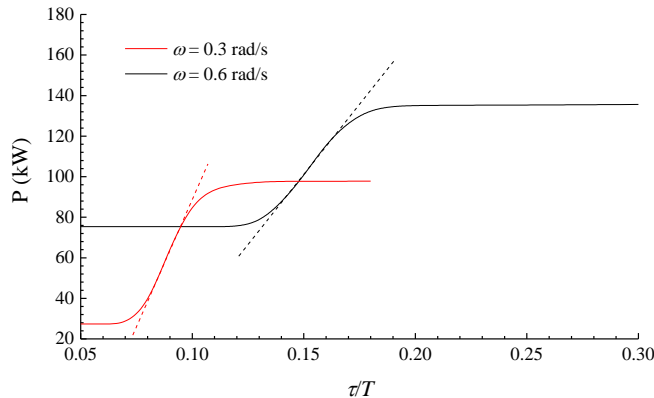


Fig. 6. Variation of average energy absorption with prediction horizon.

To interpret the mechanism behind, we plot the control sequence and the corresponding velocity in Fig. 7. When the deduction of control sequence is based on deficient prediction horizon, the latching action is seldom applied implying that the velocity phase is hardly tuned. Consequently, the response remains sinusoidal and the enhancement of energy absorption is limited. As the prediction horizon becomes longer, the deduced latching action becomes stronger. As shown in Fig. 7 (b), the WEC is locked for longer period and the tuning of velocity phase is more considerable. In this circumstance, the energy absorption is increased. When the prediction horizon is sufficiently long, the deduced control sequence is similar to that obtained by the optimal control strategy. Fig. 8 illustrates the variation of response phase with prediction horizon. The

response phase is hardly tuned with short prediction horizon. As the duration keeps increasing, the phase portrait rephrases gradually until it converges to the optimal one in the end.

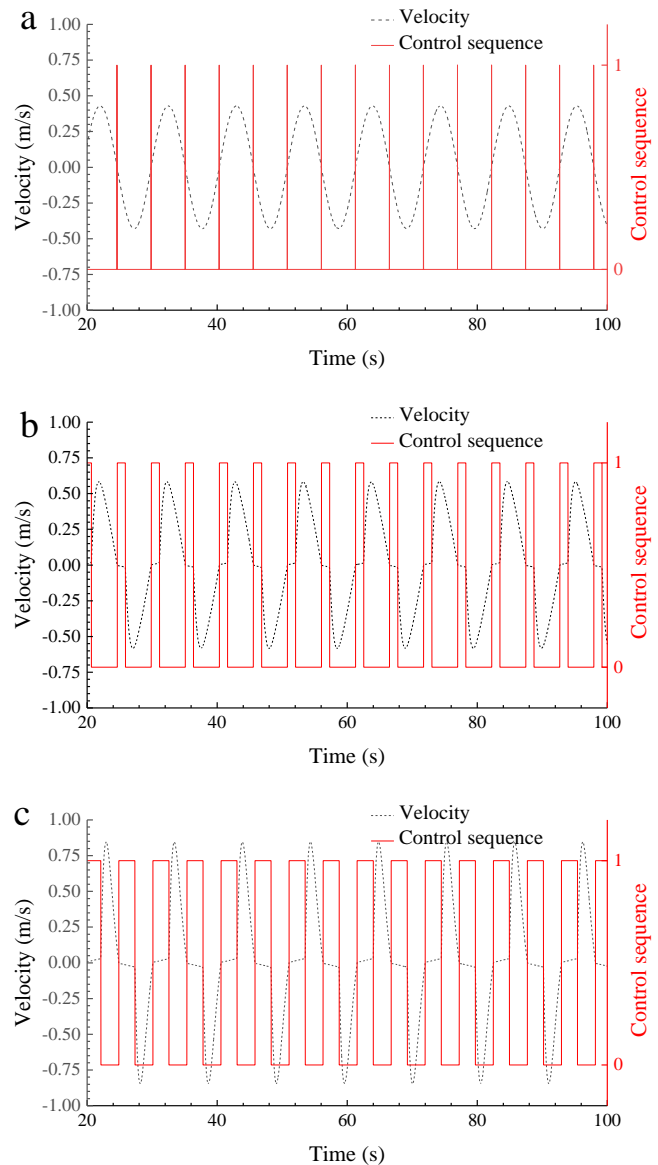


Fig. 7. Time series of velocity and control sequence, $\omega = 0.6$ rad/s. (a) $\tau = 0.1T$; (b) $\tau = 0.15T$; (c) $\tau = 0.2T$.

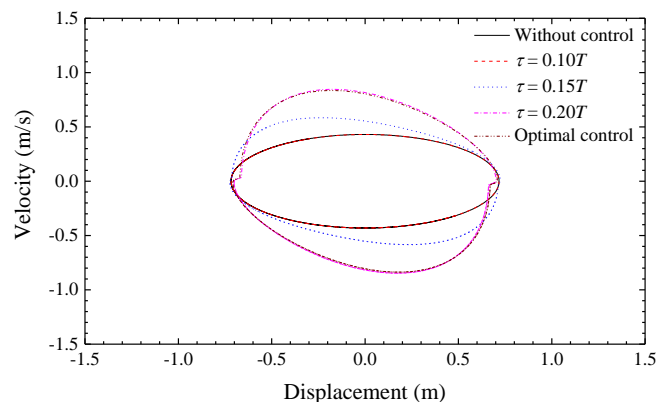


Fig. 8. Variation of phase portrait with prediction horizon, $\omega = 0.6$ rad/s.

The performance of WEC with various prediction horizons in irregular waves is listed in Table II. Similar to the performance in regular waves, the control action grows strong with prediction horizon leading to the augment of energy absorption. If the prediction horizon is sufficiently long, the real-time control can be as efficient as the optimal control.

Table II

1-HR AVERAGE ENERGY ABSORPTION				
	$\tau = 1$ s	$\tau = 1.5$ s	$\tau = 2$ s	Optimal
Case1 (kW)	24	25	26	27
Case2 (kW)	77	88	99	101
Case3 (kW)	149	176	223	229

B. Effect of prediction deviation

The above results are based on the assumption that the wave forces over the prediction horizon are known so as to eliminate the prediction deviation. Nevertheless, the wave forces in the close future must be forecasted using a prediction model in the real practice. Consequently, the prediction deviation is unavoidable and closely associated with the prediction model applied. This section will investigate the control performance with consideration of prediction deviation. According to Eq. (3), the prediction deviation can be separated into two components, namely the amplitude deviation and the phase deviation. However, it is inconvenient to evaluate the levels of the two components quantitatively given a time series of forecasted wave force, or even separate them. Considering that the prediction deviation accumulates over the prediction horizon (see Fig. 3), a long prediction horizon represents high level of prediction deviation. Therefore, the prediction duration is used to represent the prediction error qualitatively here.

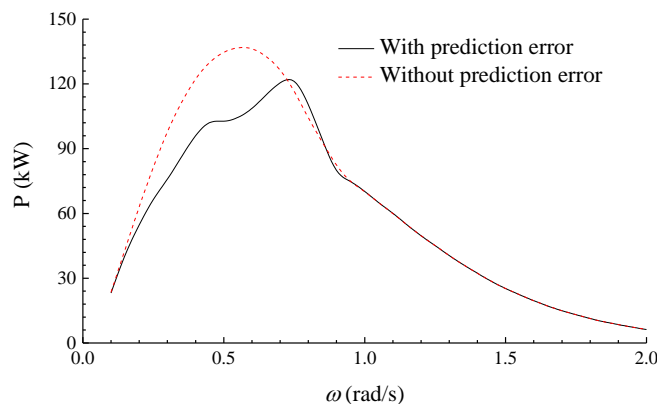


Fig. 9. Influence of prediction error on average energy absorption, $\tau = 0.2T$ (regular waves).

Fig. 9 plots the energy extraction performance of the WEC in regular waves with and without prediction deviation. Discrepancies between the two curves are observed on the left side of resonant frequency. Generally, the efficiency of real-time control is reduced in the presence of prediction deviation. To illustrate the effect of prediction deviation more clearly, the variation of energy extraction with respect to prediction horizon (a qualitative representation of prediction deviation) is plotted in Fig. 10. When the wave force prediction error is included in the real-time control strategy, the variation trend like a sigmoid curve is no longer observed although three regions are still identified. When the prediction deviation is small, it has little influence on the control performance. In the case of moderate deviation, the deviation effect on WEC performance is observed although still limited. In this region, the energy absorption still increases with the prediction horizon regardless of the accumulation of prediction deviation. As the prediction deviation continues accumulating, the energy absorption drops rapidly rather than converges to the optimal value gradually. The efficiency of real-time control is reduced significantly due to prediction deviation over this region. What's more, the real-time control even makes a negative contribution to the energy absorption in the case of notable prediction error. Similar problems were reported in [21] as well.

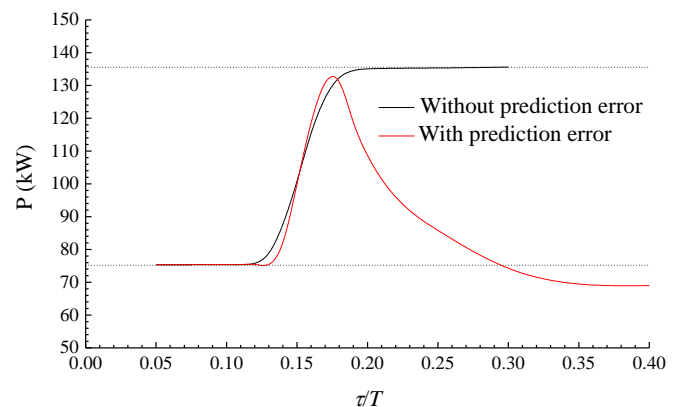


Fig. 10. Variation of average energy absorption with prediction horizon, $\omega = 0.6$ rad/s (regular waves).

Fig. 11 displays the time series of WEC velocity and control sequence with different levels of prediction deviation. When the prediction deviation is negligible, the deduction of control sequence is hardly influenced. Alongside with the accumulation of prediction deviation, the latched period and the instants at which the latching action is applied both differ. It leads to the shift to velocity phase.

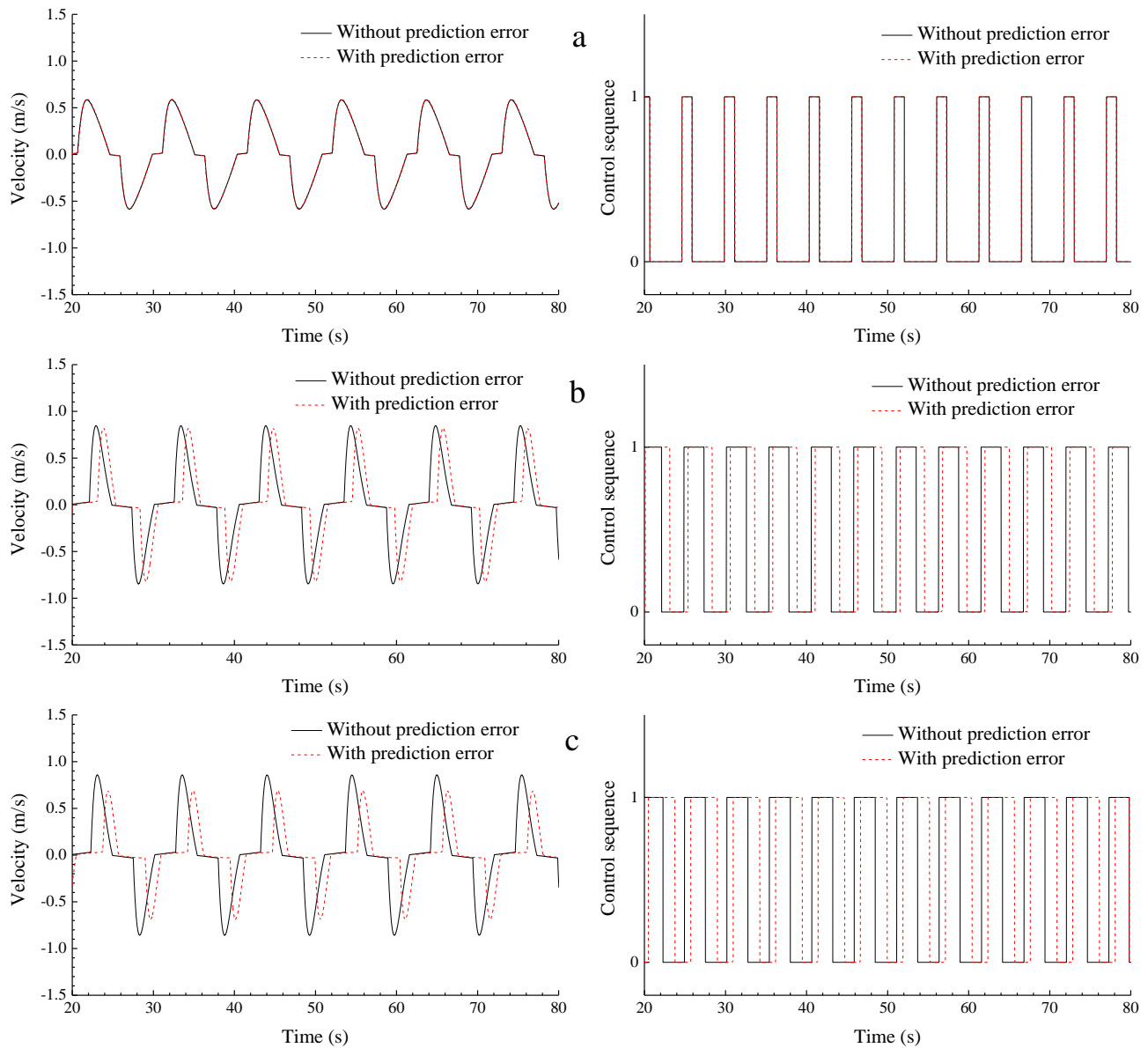


Fig. 11. Time series of velocity and control sequence, $\omega = 0.6$ rad/s. (a) $\tau = 0.15T$; (b) $\tau = 0.20T$; (c) $\tau = 0.40T$.

Using the GM(1,1) model, it is difficult to separate the phase error and the amplitude error, or estimate them quantitatively. For this purpose, we define the predicted wave forces over the prediction horizon and check the energy absorption

$$\begin{aligned}\bar{F}_{amplitude}(t) &= \text{Re} \left[\sum_{j=1}^N \alpha \psi(\omega_j) A_j e^{i(\omega_j t + \varepsilon_j)} \right] \\ \bar{F}_{phase}(t) &= \text{Re} \left[\sum_{j=1}^N \psi(\omega) A e^{i(\omega_j t + \varepsilon_j + \theta)} \right]\end{aligned}\quad (13)$$

where $\bar{F}_{amplitude}$ are the predicted wave forces involving only deviation of amplitude, \bar{F}_{phase} are the predicted wave forces involving only deviation of phase. α and θ are parameters to represent deviations of amplitude and phase, respectively. $\alpha = 1$ and $\theta = 0$ means that there is no prediction deviation. Please note that by applying Eq. (13), the wave forces over the prediction horizon are generated artificially based on the definition rather than predicted by the GM(1,1).

Fig. 12 shows the sensitivity of average energy absorption to amplitude deviation in regular waves. It is not unexpected to find that the energy absorption performance varies hardly with the amplitude deviation. As discussed above, the latching is a kind of phase control so that amplitude deviation will have little influence on the control sequence deduction. The amplitude deviation will only influence the amplitudes of velocity and state vector λ whereas the signs are not reversed. Therefore, the control sequence nearly remains the same according to Eq. (6) and the energy absorption varies little.

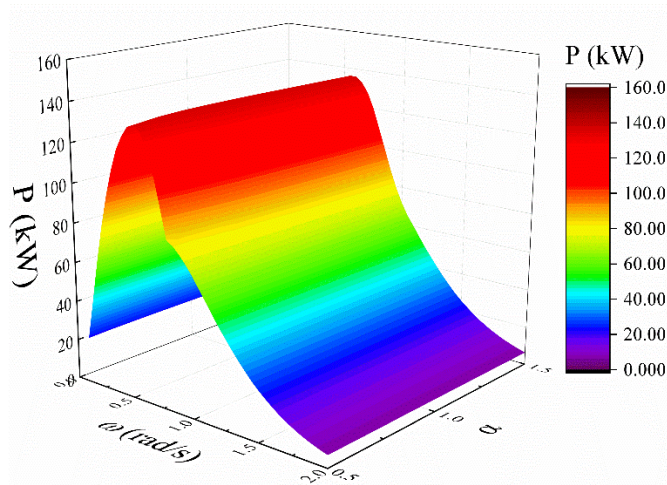


Fig. 12. Influence of amplitude deviation on the energy absorption in regular waves, $\tau = 0.2T$.

Fig. 13 displays the average energy absorption in regular waves considering the deviation of phase. It can be seen that the effect of phase deviation on average energy absorption is significant. In high frequency range, the contour is relatively flat since the optimal command theory cannot find the solution in this region [10, 12]. Consequently, the control law is equal to zero even in the presence of prediction deviation. The maximum energy absorption is achieved at $\theta = 0$ in the absence of phase deviation. As the phase deviation extends, the energy absorption drops rapidly. Besides, the contour surface is nearly symmetric with respect to $\theta = 0$.

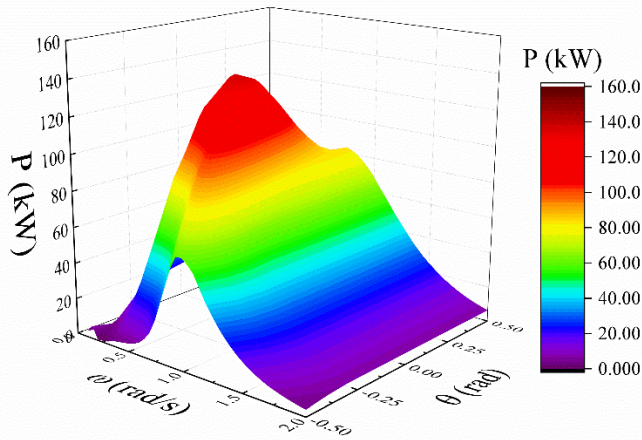


Fig. 13. Influence of phase deviation on the energy absorption in regular waves, $\tau = 0.2T$.

Fig. 14 shows the influence of phase deviation on the control performance. As shown, the control sequence is very sensitive to the phase deviation. When the phase deviation expands, the latched duration shrinks indicating that the control action becomes weaker. In this circumstance, the velocity phase is only tuned slightly. Moreover, the latching action is applied earlier than it should be with the consideration of phase deviation. It implies that the WEC is locked when it should be released. Due these factors, the efficiency of the real-time control is reduced with the phase deviation.

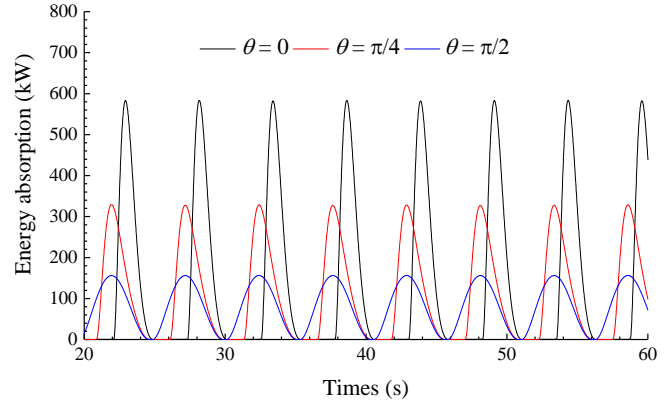
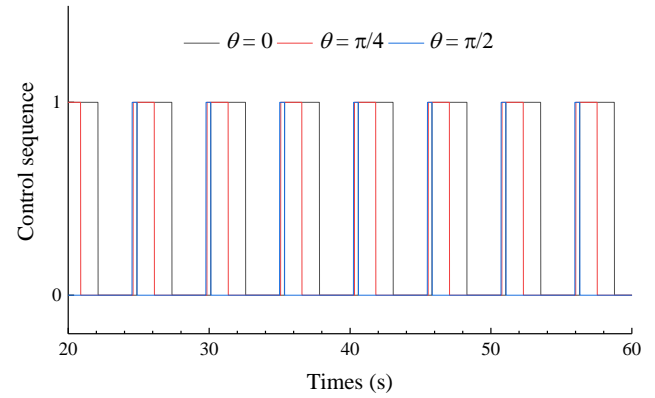


Fig. 14. Influence of phase deviation on energy absorption in regular waves, $\omega = 0.6$ rad/s.

The effect of phase deviation on the energy absorption in irregular waves is shown in Table III. In irregular waves (Case3), the energy absorption also drops as the phase error increases.

Table III			
Average energy absorption in Case3 ($\tau = 2$ s)			
	$\theta = 0$	$\theta = \pi/8$	$\theta = \pi/4$
P	223 kW	214 kW	188 kW

Fig. 15 shows how the phase deviation affects the control sequence. In the presence of phase deviation, the controller makes an improper judgement on whether lock the WEC or not. As shown, the WEC is locked and released at the wrong instants. In the meanwhile, the WEC velocity is not increased adequately as a result of the phase deviation. (see Fig. 16).

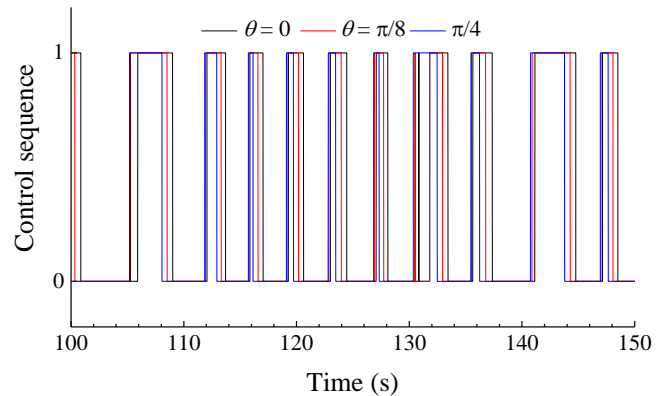


Fig. 15. Influence of phase deviation on the control sequence in irregular waves (Case3).

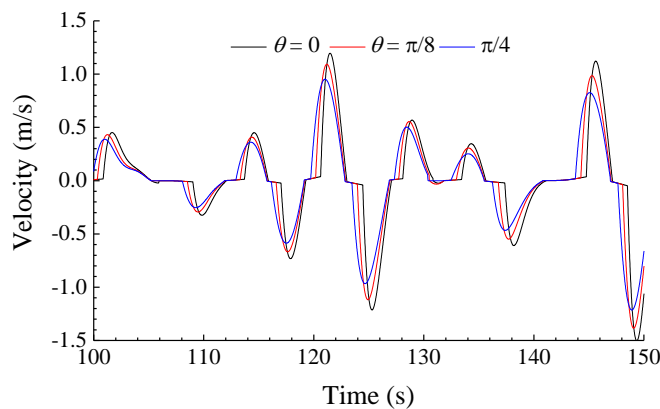


Fig. 16. Influence of phase deviation on controlled velocity in irregular waves (Case3).

V. CONCLUSION

A real-time latching control with consideration of wave force prediction is applied to a heaving point-absorber WEC to enlarge the energy extraction. The real-time control strategy is based on the combination of optimal command theory and first order-one variable grey model GM(1,1). By forecasting the wave forces over the coming future, the prediction effect is considered. This study focuses on how the two essential aspects of wave force prediction, namely horizon and deviation, influence the energy absorption of the point-absorber.

A long prediction horizon is beneficial to energy absorption in the absence of prediction deviation. Generally, the variation of energy extraction to the prediction horizon follows a sigmoid function. When the prediction horizon is very short, the energy absorption varies hardly with the prediction horizon. Within this region, the expansion of prediction horizon will not have any effects on the control performance. In the case of moderate prediction horizon, the energy absorption becomes very sensitive to the prediction horizon and increases rapidly with it. As the prediction horizon keeps increasing, the run-up of energy absorption gradually slows down and converges to the optimal value finally. Besides, it is found that the WEC is more sensitive to the prediction horizon in long waves.

Since a true real-time control must forecast the wave forces with a selected prediction model, the associated prediction deviation is unavoidable. When a prediction model is used, the prediction deviation accumulates over the prediction horizon. Simulation results show that the efficiency of the PTO system is reduced with the consideration of prediction deviation. Moreover, the energy absorption in the presence of notable prediction deviation is even lower than that without latching control. To clarify the effects of prediction deviation, the forecasted wave forces are pre-defined artificially to separate the amplitude deviation and the phase deviation. It is shown the amplitude deviation has a very little influence on WEC performance as latching control is by nature a kind of phase control. Nevertheless, the energy absorption drops considerably with the expansion of phase deviation, especially within the low wave frequency range.

Since a long prediction horizon is beneficial to the energy absorption whereas the prediction deviation accumulates over the horizon, a moderate prediction horizon is thus recommended for the application of a real-time control with

consideration of wave force prediction.

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Liang Li received his B.S. and M.Sc. degrees from Shanghai Jiao Tong University. He is now a Ph.D. student in University of Strathclyde. His research topic is mainly relating renewable energy, with a focus on the wave energy converter control.

Zhiming Yuan received his B.S. and M.Sc. degrees from Jiangsu University of Science and Technology. After completing this Ph.D. study in University of Strathclyde, he stayed and worked as a lecturer until now. His research area includes multi-body hydrodynamic interaction and renewable energy.

Yan Gao received her B.S. and M.Sc. degrees from Shanghai Jiao Tong University. Now, she is working towards her Ph.D. degree in University of Strathclyde. Her research interest mainly focuses on renewable energy, in term of structural integrity.

Xinshu Zhang obtained his B.S. and M.Sc. degrees from Shanghai Jiao Tong University. After that, he went to the University of Michigan, where he received his Ph.D degree. Currently, he is a professor in Shanghai Jiao Tong University after years of service in the marine industry. His research interest includes nonlinear wave-structure interaction, design of marine structures.